Sparse-Recovery-Based Channel Estimation in Orthogonal Time-Frequency Space Modulation for High-Mobility Scenarios in 5G and Beyond

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***Abstract*—Orthogonal time frequency space (OTFS) modulation is a breakthrough waveform that significantly outperforms conventional modulation schemes in high-mobility scenarios. Unlike traditional approaches that operate in the time-frequency domain, OTFS exploits the delay-Doppler domain, transforming a time-varying channel into a nearly time-invariant one. This paper focuses on the critical challenge of channel estimation (CE) in OTFS-based downlink communication. Recognizing the inherent sparsity of the delay-Doppler domain, the CE problem is formulated as a sparse recovery task, enabling the use of advanced compressed sensing techniques. A robust greedy algorithm, namely multipath matching pursuit (MMP), is aided for OTFS to enhance estimation accuracy. The effectiveness of MMP is benchmarked against orthogonal matching pursuit (OMP) and conventional impulse-based estimation methods. Simulation results demonstrate that the proposed MMP-based CE technique significantly improves channel state information acquisition and achieves superior normalized mean square error performance, making it a promising solution for high-mobility 5G and beyond communication systems.**

***Index Terms*—Channel estimation, compressed sensing, delay-Doppler, OTFS modulation, sparse channel recovery.**

I. Introduction

The fifth generation of wireless communication (5G and beyond) requires seamless and reliable communication in highly mobile scenarios such as communication between vehicles (V2V), communication between vehicles and various entities (V2X), high-speed train networks, applications utilizing millimeter wave (mmWave) technology, unmanned aerial vehicles (UAVs), and aircraft [1]–[3]. In channels characterized by double dispersion, the performance of orthogonal frequency division multiplexing (OFDM) is hindered primarily attributed to the diminished orthogonality among sub-carriers [4]. Orthogonal time frequency space (OTFS) is an upcoming modulation scheme that demonstrates resilient performance in high Doppler environments [5], [6]. OTFS works in the 2D delay-Doppler (DD) domain, providing a more precise physical representation of the mobile channel. In OTFS, the information symbols are multiplexed and the channel is depicted in the DD domain due to which a time-varying channel looks approximately time-invariant. As the channel seems to be stationary for a longer duration in the DD domain, it is sparsely represented in nature and requires very less parameters to be estimated. This underlying sparsity is the key parameter in simplifying the channel estimation (CE) problem in the DD domain when compared to the time-frequency domain. Several works on the OTFS CE have been reported in the literature [7]–[16] for high-mobility environments which can be segregated into two categories: pilot and compressed sensing-based CE.

In pilot-based approach the CE is carried out by aiding pilot symbols which are transmitted either as a standalone or superimposed or embedded with information. In reference [7], within every OTFS frame, a strategic arrangement of data symbols, pilot, and guard is implemented in the DD plane, effectively minimizing pilot and data symbols' interference at the receiver. Also, specific arrangements of symbols tailored for OTFS operating in multipath channels with both fractional and integer Doppler shifts are made. In the receiver stage, CE employs a threshold technique. The acquired channel information is subsequently applied in the detection of data through the implementation of a message-passing algorithm. A novel pilot-based time-domain CE technique is presented in [8], specifically designed for cyclic prefix (CP)-OTFS systems and embedded in the DD domain. This method addresses challenges posed by fractional multiple Doppler effects, residual frame timing offset, and carrier frequency offset. Additionally, a low-complexity linear minimum mean square error (MMSE) equalization and successive interference cancellation (SIC) receiver designed for low-density parity check (LDPC) coded CP-OTFS systems are analyzed.

Moreover, a compressed sensing (CS) based greedy algorithm is introduced in [9], a novel approach to CE, leveraging a 3D-structured orthogonal matching pursuit (OMP) algorithm. This technique is specifically tailored to address the complexities of the OTFS multiple input multiple output

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(MIMO) channel. Initially, the OTFS MIMO channel 3D-structured sparsity is framed, characterized by the sparsity, block sparsity, and burst sparsity along the delay, Doppler, and angle dimensions, respectively. Utilizing this structured sparsity, the formulation of the downlink CE task as a problem of recovering a sparse signal is accomplished. Likewise, algorithms based on OMP and modified subspace pursuit (MSP) for DD CE in the uplink OTFS system are exploited in [10]. The study includes a comparative analysis of the performance of these estimation techniques based on CS against the impulse-based CE scheme commonly reported in OTFS. The proposed compressed sensing CS-based algorithms demonstrate superior performance compared to the impulse-based CE scheme, as evidenced by the normalized mean squared error and bit error performance. Also, an off-grid CE method for OTFS systems, utilizing the sparse Bayesian learning (SBL) and block SBL framework is proposed in [11], [12]. These approaches aim to mitigate channel fading induced by Doppler shifts and fractional delay by estimating the response of the original DD domain channel rather than that of the effective DD domain channel. These techniques employ a virtual sampling grid specified in the DD space to acquire the on-grid and off-grid components of delay and Doppler shifts during the estimation process. Subsequently, the determination of on-grid and off-grid components is carried out by locating the entry indices having significant values in the reconstructed sparse vector and hyper parameters within the proposed SBL framework, respectively which is estimated using the expectation-maximization method.

An algorithm comprising two stages is designed for determining the fractional Doppler channels, which is proposed in [13]. At the outset, an approximate position for every non-zero Doppler shift is determined by correlating the basis function in the DD domain. Subsequently, a quasi-Newton method is aided to iteratively enhance the fractional Doppler channel estimation, depending on the initial estimation which reduces the estimation error attributable to inter-delay interference (IDI). In [14], a less complex CE algorithm with a rapid greedy sparse recovery method termed two-choice hard thresholding pursuit (TCHTP) is introduced. This algorithm is designed to estimate DD locations and the corresponding channel state information (DDLCSI) within OTFS systems, even in the absence of explicit knowledge regarding the number of DD paths. The proposed approach exhibits superior performance compared to conventional methods in mean square error, number of DD path estimates, and complexity. Substantial works on CE for OTFS are listed out in [15] with highlights and challenges of each technique.

In light of this, the key factor for the OTFS CE is the sparse nature of the channel which should be taken into account. Due to this sparse characteristic, the CE problem is conceptualized as a challenge in sparse signal recovery, which can be solved using CS-based algorithms [16]–[19]. In this paper, a greedy CS algorithm viz., multipath matching pursuit (MMP) is aided for estimating the OTFS MIMO channel in the downlink scenario. MMP employs a tree search with the assistance of a greedy strategy to address the sparse recovery problem. Moreover, the dual functionality of MMP i.e., depth-first (DF) and breadth-first (BF) search techniques are analyzed. The foremost contributions of this paper are:

- An MMP-based CE framework is employed for OTFS, leveraging the sparsity of the DD domain to enhance signal recovery and improve estimation accuracy in high-mobility environments.
- Provides a comparative study of DF-MMP and BF-MMP approaches, demonstrating DF-MMP's superior accuracy in normalized mean square error (NMSE) under practical system conditions.
- Contrasts MMP with OMP and impulse-based estimation methods, highlighting MMP's significant advantages in precision, robustness, and adaptability for OTFS-based communication.
- Also, investigates the impact of key parameters such as antenna configurations, pilot overhead ratio, and user velocity, offering deep insights into performance trade-offs in dynamic wireless environments.
- Aligns with the evolving demands of 5G and beyond, providing a scalable and efficient CE solution for OTFS in high-mobility scenarios, ensuring improved reliability and network efficiency.

The far comparative analysis of MMP, OMP, and impulse-based methods for OTFS CE highlights key distinctions in their approach and efficiency. MMP effectively exploits the sparsity of the DD domain by employing a structured search mechanism. It iteratively refines path estimation through DF or BF strategies, where DF MMP quickly identifies dominant paths, and breadth-first MMP provides a more stable and comprehensive solution. OMP, though also a greedy algorithm, lacks a structured multipath exploration strategy, which can lead to sub-optimal CE in complex environments. Impulse-based methods, being a straightforward approach, do not leverage sparsity and rely solely on direct pilot-based estimation, making them less effective in handling multipath and Doppler shifts. In terms of efficiency, MMP offers superior estimation accuracy by effectively identifying and tracking multipath components, while OMP provides moderate performance with simpler implementation but lacks refined path selection. Impulse-based methods, though computationally less demanding, suffer from significant performance degradation in high-mobility scenarios. MMP's structured approach makes it more adaptable and robust, ensuring reliable CE essential for OTFS-based wireless communication. Simulation results signify that the MMP-based CE technique achieves enhanced NMSE in comparison to OMP and impulse-based techniques.

The rest of the paper is organized as follows. Section II provides the relevant input-output relationship equations of the OTFS system. The DF and BF-MMP-based estimation schemes for OTFS MIMO in downlink are described in Section III. The simulation results and discussions are gathered in Section IV with drawn conclusions in Section V.

Notations: Boldface capital letters denote matrices and lower-case letters denote column vectors. The inverse of a matrix, transpose, conjugate and conjugate transpose are denoted by $(\cdot)^{-1}$ $(\cdot)^T$, $(\cdot)^*$ and $(\cdot)^H$, respectively. $\odot$ denotes the Hadamard product operator.

II. OTFS System Model and its Mathematical Background

Consider an OTFS massive MIMO system model, where the base station is equipped with N_t transmit antennas to accommodate U users with a single receiver antenna. The quadrature amplitude modulated (QAM) information symbols of length MN are arranged into an $M \times N$ 2D DD grid Γ to obtain 2D OTFS frame $\mathbf{X}^{\mathrm{DD}} \in \mathbb{C}^{M\times N}$ in the DD domain. Γ is given as,

$$\Gamma = \left\{ \left(\frac{k}{NT}, \frac{l}{m\Delta f} \right), k = 0, 1, \ldots, N-1; \right. \\ \left. l = 0, 1, \ldots, M-1 \right\} \quad (1)$$

where $\frac{1}{m\Delta f}$ and $\frac{1}{NT}$ are the quantization steps in the delay and Doppler axes while M and N are the number of DD resource block (DDRB) in the delay and Doppler dimensions, respectively. For ensuring maximum multi-user (MU)-MIMO capacity and in order to eliminate the inter-user interference downlink precoding is performed. After precoding, the 2D inverse symplectic finite Fourier transform (ISFFT) along with transmit windowing is applied, in order to translate these symbols from DD grid Γ to time-frequency grid given by Λ. The TF plane is discretized by sampling time axes at interval T and the frequency axes at interval Δf to obtain a $M \times N$ grid Λ given by,

$$\Lambda = \{(nT, m\Delta f)\,,\ n = 0, 1, \ldots, N-1; \\ m = 0, 1, \ldots, M-1\} \quad (2)$$

ISFFT is equivalent to M-point FFT of the columns and N-point IFFT of the rows of $\mathbf{X}^{\mathrm{DD}}$. Thus, the symbols obtained after ISFFT, $\mathbf{X}^{\mathrm{ISFFT}} \in \mathbb{C}^{M\times N}$, is written as [6],

$$\mathbf{X}^{\mathrm{ISFFT}} = \mathbf{F}_M \mathbf{X}^{\mathrm{DD}} \mathbf{F}_N^{\mathrm{H}} \quad (3)$$

where $\mathbf{F}_M$ is the M-point discrete Fourier transform (DFT) matrix, and $\mathbf{F}_N^{\mathrm{H}}$ is the N-point inverse discrete Fourier transform (IDFT) matrix. The symbol $\mathbf{X}^{\mathrm{ISFFT}}$ is then multiplied element-wise with the transmit windowing matrix $\mathbf{W}^{\mathrm{tx}}$ to obtain $\mathbf{X}^{\mathrm{TF}} \in \mathbb{C}^{M\times N}$, the symbol in the TF domain, given as,

$$\mathbf{X}^{\mathrm{TF}} = \mathbf{X}^{\mathrm{ISFFT}} \odot \mathbf{W}^{\mathrm{tx}} \quad (4)$$

The Heisenberg transform operates on $\mathbf{X}^{\mathrm{TF}}$ using an M-point IFFT along with the pulse shaping waveform $\mathrm{g}_{\mathrm{tx}}(t)$ to map the 2D DD symbol onto the time domain signal $\mathbf{S} \in \mathbb{C}^{M\times N}$, in order to transmit over the time-varying channel. The signal to be transmitted is given by,

$$\mathbf{S} = \mathbf{G}_{\mathrm{tx}} \mathbf{F}_M^{\mathrm{H}} \mathbf{X}^{\mathrm{TF}} \quad (5)$$

where $\mathbf{G}_{\mathrm{tx}} \in \mathbb{C}^{M\times M}$ is a diagonal matrix containing the samples of $\mathrm{g}_{\mathrm{tx}}(t)$, and $\mathbf{F}_M^{\mathrm{H}}$ is the M-point IDFT matrix. If a rectangular pulse shaping function is considered, $\mathbf{G}_{\mathrm{tx}}$ reduces to the identity matrix. By combining (3) to (5), the transmit signal can be written as,

$$\mathbf{S} = \mathbf{X}^{\mathrm{DD}} \mathbf{F}_N^{\mathrm{H}} \quad (6)$$

Each symbol in $\mathbf{S}$ has a cyclic prefix (CP) of length N_{CP} appended to it, using the CP addition matrix $\mathbf{A}_{\mathrm{CP}} \in \mathbb{C}^{(M+N_{\mathrm{CP}})\times M}$ for the prevention of inter-symbol interference (ISI). By the column-wise vectorization of $\mathbf{S}$, the 1D time domain transmitted signal $\mathrm{s} \in \mathbb{C}^{(M+N_{\mathrm{CP}})N\times 1}$ is obtained,

$$\mathbf{s} = \mathrm{vec}\{\mathbf{A}_{\mathrm{CP}}\mathbf{S}\} \quad (7)$$

A. Channel

The signal $s(t)$ is transmitted through the time-variant channel after parallel-to-serial and digital-to-analog conversion of $\mathbf{s}$. The i^{th} element of the received signal $\mathbf{r} \in \mathbb{C}^{(M+N_{\mathrm{CP}})N\times 1}$, which is converted back to digital from $r(t)$, can be given as,

$$r_i = \sum_{p=0}^{P} h_{i,p} s_{i-p} + v_i \quad (8)$$

where $P+1$ is the length of the time-variant channel $h_{i,p}$ and v_i is the additive noise.

B. Receiver

At the receiver, the received symbol $\mathbf{r}$ is converted back to a 2D block in the TF domain by arranging it into a matrix $\mathbf{R} \in \mathbb{C}^{(M+N_{\mathrm{CP}})N\times 1}$, in which each column vector of $\mathbf{R}$ is a symbol with the CP appended to it.

$$\mathbf{R} = \mathrm{invec}\{\mathbf{r}\} \quad (9)$$

CP removal is carried out by multiplying $\mathbf{R}$ with the CP removal matrix given by $\mathbf{R}_{\mathrm{CP}} \in \mathbb{C}^{M\times(M+N_{\mathrm{CP}})}$. The Wigner transform, the inverse of the Heisenberg transform, is applied on the symbols after the removal of CP. It operates by taking the M-point FFT on the column vectors of $\mathbf{R}_{\mathrm{CP}}\mathbf{R}$ to obtain $\mathbf{Y}^{\mathrm{TF}}$, given as,

$$\mathbf{Y}^{\mathrm{TF}} = \mathbf{F}_M \mathbf{R}_{\mathrm{CP}} \mathbf{R} \quad (10)$$

where $\mathbf{F}_M$ is the M-point DFT matrix. The conversion of the 2D symbols from the TF to DD domain is done using receive windowing and the symplectic fast Fourier transform (SFFT). Receive windowing is carried out by the element-wise multiplication of $\mathbf{Y}^{\mathrm{TF}}$ with the window matrix $\mathbf{W}^{\mathrm{rx}}$, given as,

$$\mathbf{Y}^{\mathrm{W}} = \mathbf{Y}^{\mathrm{TF}} \odot \mathbf{W}^{\mathrm{rx}} \quad (11)$$

Subsequently, the SFFT, which is the M-point IFFT of the columns and the N-point FFT of the rows of $\mathbf{Y}^{\mathrm{W}}$, is applied to obtain the symbol $\mathbf{Y}^{\mathrm{DD}}$ in the 2D SD domain, which can be written as,

$$\mathbf{Y}^{\mathrm{DD}} = \mathbf{F}_M^{\mathrm{H}} \mathbf{Y}^{\mathrm{W}} \mathbf{F}_N \quad (12)$$

C. Input-Ouput Relationships

From [9], the 2D received information block can be interpreted as the two-dimensional periodic convolution between the 2D DD transmit symbol $\mathbf{X}^{\mathrm{DD}}$ and the DD channel impulse response (CIR) $\mathbf{H}^{\mathrm{DD}} \in \mathbb{C}^{M\times N}$. Let $\mathbf{X}^{\mathrm{DD}}_{l,k}$ and $\mathbf{Y}^{\mathrm{DD}}_{l,k}$ be the $(l+1, k+1+\frac{N}{2})^{\mathrm{th}}$ elements of the transmit and receive signals $\mathbf{X}^{\mathrm{DD}}$ and $\mathbf{Y}^{\mathrm{DD}}$, where $l = 0, 1, \ldots, M-1$ and $k = -\frac{N}{2}, \ldots, 0, \ldots, \frac{N}{2}-1$. Then the input-output relation can be written as [6],

$$\mathbf{Y}^{\mathrm{DD}}_{l,k} \overset{N\to\infty}{=} \sum_{l'=0}^{M-1} \sum_{k'=-\frac{N}{2}}^{\frac{N}{2}-1} \mathbf{X}^{\mathrm{DD}}_{l',k'} \mathbf{H}^{\mathrm{DD}}_{l-l',k-k'} e^{j2\pi \frac{l(k-k')}{N(M+N_{\mathrm{CP}})}} + \mathbf{V}^{\mathrm{DD}}_{l,k} \quad (13)$$

where $\mathbf{H}^{\mathrm{DD}}_{l,k}$ is the $(l+1, k+1+\frac{N}{2})^{\mathrm{th}}$ element of the DD CIR $\mathbf{H}^{\mathrm{DD}}$ and $\mathbf{V}^{\mathrm{DD}}_{l,k}$ is the additive noise in the DD domain. Finally, equalization is to be carried out to avoid ISI, for which the DD CIR $\mathbf{H}^{\mathrm{DD}}$ is necessary. Downlink channel estimation is employed at the receiver for determining the CIR $\mathbf{H}^{\mathrm{DD}}$.

III. CHANNEL ESTIMATION

CE in OTFS systems involve estimating the characteristics of the wireless channel through which signals are transmitted. This process is crucial for accurately recovering transmitted data symbols at the receiver, especially in scenarios with multipath propagation, and Doppler shifts. In OTFS, the DD domain is utilized for signal representation, where delays represent the time-domain and Doppler shifts represent the frequency-domain. In OTFS systems, the channel impulse response in the DD domain is predominantly composed of zeros, with only a few non-zero coefficients and is sparse in nature. This sparsity arises due to the propagation characteristics of wireless channels, especially in scenarios with sparse scattering environments or when the channel can be represented effectively using a small number of paths. The sparsity in the OTFS channel can be leveraged for efficient CE and equalization. By exploiting the sparse nature of the channel impulse response, the complexity of CE algorithms can be reduced which improves their performance, leading to more robust communication systems. The undetermined system with sparsity is subject to minimization function and can be mathematically expressed as,

$$\min_{\mathrm{X}} \|\mathrm{X}\|_2 \quad \text{for} \quad \Psi\mathrm{X} = \mathrm{Y}, \quad (14)$$

where Ψ denotes the measurement matrix or the sensing matrix in the compressed sensing algorithm, X represents the original or underlying signal that needs to be recovered or reconstructed, and Y denotes the measurements or observations obtained through the sensing process. This equation aims to minimize the error function and tries to achieve exact recovery of the sparse information. In the context of this, an effective sparse recovery greedy algorithm is necessary to make the system determined from its undetermined nature. MMP [20]–[23] is a highly effective sparse recovery algorithm that plays a crucial role in channel CE for OTFS modulation, particularly in high-mobility and frequency-selective fading scenarios. The key advantage of OTFS over traditional time-frequency domain modulation lies in its ability to represent the wireless channel in the DD domain, where the channel exhibits natural sparsity. This sparsity makes CS-based CE techniques essential for accurate signal reconstruction. Among the available CS-based approaches, MMP provides a significant advantage over traditional methods, such as impulse-based techniques and OMP, by offering superior signal recovery capabilities while maintaining computational efficiency [24]–[26]. Traditional CE techniques, such as impulse-based methods, rely on direct correlation with known pilot signals to estimate the channel impulse response. However, they suffer from high pilot overhead, reduced estimation accuracy, and degraded performance in complex propagation conditions. OMP, another commonly used greedy algorithm for sparse signal recovery, performs single-index selection per iteration, making it prone to incorrect index choices that propagate errors throughout the estimation process. Moreover, OMP's sequential processing leads to increased computational time as sparsity grows, making it inefficient for large-scale OTFS systems. In contrast, MMP effectively mitigates these issues by refining its search strategy to handle multiple overlapping signal components. Unlike OMP, MMP dynamically selects multiple indices per iteration, improving estimation accuracy and convergence speed. This makes MMP particularly suitable for OTFS, where the inherent sparsity of the DD domain requires a robust and flexible estimation technique. By iteratively decomposing the received signal into a linear combination of basis functions. These basis functions can represent various characteristics of the signal, such as time delay, frequency, or direction of arrival. MMP ensures that the most significant components are identified and refined, enabling more accurate CE with reduced computational overhead. MMP also offers a significant improvement in computational complexity over traditional methods. Since OMP makes hard decisions at each iteration, a single incorrect selection can lead to severe estimation errors, resulting in inaccurate CSI acquisition. Additionally, if the correlation between dictionary elements is high, OMP takes the maximum number of iterations to converge, increasing computational burden. MMP, however, adopts a more flexible search strategy, reducing error propagation and enhancing overall robustness. To further optimize MMP for OTFS CE, two variations viz., DF-MMP and BF-MMP have been studied. DF-MMP prioritizes one dominant path at a time, exploring its depth before moving on to alternative paths, making it efficient when dominant components can be identified early. While BF-MMP explores multiple paths simultaneously, ensuring a more exhaustive search of the DD domain at the cost of increased computational effort. The choice between the two approaches may depend on factors such as the sparsity of the signal, the structure of the basis function dictionary, and computational considerations. In this paper, both techniques are studied and the performance analysis is observed in terms of NMSE. A detailed comparison of MMP, OMP, and impulse-based techniques was conducted to assess their suitability for OTFS CE.

A. Depth-First MMP

DF-MMP [21] is a structured greedy algorithm designed for efficient sparse recovery, particularly suited for OTFS CE. OTFS modulation represents the wireless channel in the DD domain, where the channel impulse response exhibits inherent sparsity due to the limited number of significant multipath components. The estimation challenge lies in accurately recovering the channel coefficients while maintaining computational efficiency, especially in high-mobility environments where Doppler shifts significantly impact signal quality. DF-MMP effectively addresses this challenge by leveraging a structured search strategy that prioritizes dominant signal components and iteratively refines the channel estimate. The step-by-step procedure for DF-MMP-based CE is outlined in Algorithm 1.

The DF-MMP algorithm begins by selecting an initial basis function from a predefined dictionary that best matches the most significant component of the residual signal. This dictionary contains basis functions that represent key OTFS system parameters, such as time delay (τ), Doppler shift (υ), and channel gain (h). In OTFS, the received signal in the DD domain is modeled as a sparse linear combination of these basis functions, making it suitable for CS-based recovery methods like MMP. The basis function selection in DF-MMP is guided by an inner product operation, where the function that maximally correlates with the residual signal is chosen. Since OTFS exhibits multipath sparsity, selecting the most dominant component first ensures that the strongest contributors to the received signal are accurately identified.

Once the most relevant basis function is chosen, DF-MMP follows a depth-first exploration strategy, which means it further refines the estimate along the same path before considering alternative basis functions. This process is analogous to traversing a tree structure, where the algorithm goes as far down a single branch as possible before backtracking and exploring alternative branches. The advantage of this approach in OTFS CE is that dominant channel components such as strong line-of-sight (LoS) paths or primary reflectors are estimated with high accuracy before moving to weaker multipath components. Since OTFS operates with a large number of delay-Doppler grid points, this structured search helps in reducing the overall computational complexity while maintaining estimation precision. A critical aspect of DF-MMP is its iterative refinement process. After selecting a basis function, the algorithm updates the channel estimate by solving an optimization problem that minimizes the difference between the selected basis function and the corresponding portion of the residual signal. This step ensures that the estimated channel coefficients align closely with the received signal structure. Following this, the contribution of the selected basis function is subtracted from the residual signal, and the process is repeated iteratively. The stopping criterion for DF-MMP is either reaching a predefined maximum number of iterations or when the residual signal falls below a certain threshold, indicating that all significant channel components have been recovered. DF-MMP offers computational efficiency in OTFS CE due to its structured path selection strategy. Unlike traditional greedy methods like OMP, which select a single index per iteration without considering structured relationships between components, DF-MMP prioritizes the strongest contributions early in the estimation process. This is particularly beneficial in OTFS systems with dominant direct paths or well-separated multipath components, as the algorithm can efficiently capture the most significant delays and Doppler shifts while reducing unnecessary computations.

Furthermore, DF-MMP's backtracking mechanism enables the exploration of alternative basis functions when the current path does not contribute significantly to the channel estimate. This feature ensures that the algorithm does not get stuck in suboptimal selections, thereby improving the robustness of the estimation process. Since OTFS channels experience varying sparsity levels depending on mobility conditions and pilot overhead, DF-MMP dynamically adapts its search strategy to optimize performance.

Algorithm 1 MMP-DF

Input: Measurement $\mathbf{y}$, sensing matrix $\mathbf{\Psi}$, sparsity K, number of expansion L, stop threshold ϵ, maximum number of search candidates $\ell_{\max}$
Output: Estimated signal $\hat{\mathbf{h}}$
Initialization: $\ell := 0$ (candidate order), $\rho := \infty$ (min. magnitude of residual), $r^0 := y$ (initial residue)
while $\ell < \ell_{\max}$ **and** $\epsilon < \rho$ **do**
  $\ell := \ell + 1$
  $r^0 := y$
  $[c_1, \ldots, c_K] := \text{compute\_ck}(\ell, L)$
  for $k = 1$ **to** K **do**
    $\widetilde{\pi} := \arg\max_{|\pi|=L} \|(\mathbf{\Psi}'\mathbf{r_i}^{\mathbf{k-1}})_\pi\|_2^2$
    $\Omega_\ell^k := \Omega_\ell^{k-1} \cup \{\widetilde{\pi}_{C_k}\}$
    $\widehat{\mathbf{h}}^k := \Phi^\dagger_{\Omega_u^k}\mathbf{y}$
    $\mathbf{r}^k := \mathbf{y} - \Phi^\dagger_{\Omega_\ell^k}\widehat{\mathbf{h}}^k$
  end for
  if $|\mathbf{r}^K| < \rho$ **then**
    $\rho := |\mathbf{r}^K|$
    $\hat{\mathbf{h}}^* := \hat{\mathbf{h}}^K$
  end if
end while
return $\hat{\mathbf{h}}^*$

function `compute_ck` (ℓ, L)
  $\text{temp} := \ell - 1$
for $k = 1$ **to** K **do**
  $C_k := \text{mod}(\text{temp}, L) + 1$
  $\text{temp} := \text{floor}\left(\frac{\text{temp}}{L}\right)$
end for
return $[c_1, \ldots, c_K]$
end function

B. Breadth-First MMP

BF-MMP is an advanced extension of the MMP algorithm tailored for efficient sparse recovery in OTFS CE. Unlike DF-MMP, which sequentially refines a single path before considering alternatives, BF-MMP simultaneously explores multiple paths at the same level of the DD domain, ensuring a comprehensive search before proceeding to deeper levels. This exploration strategy aligns with breadth-first traversal in graph theory, making it particularly effective for OTFS systems, where multipath components are spread across the DD plane. The step-by-step process of BF-MMP-based CE is detailed in Algorithm 2. OTFS modulation operates in the DD domain, where channel sparsity is exploited to improve CE performance. In this context, BF-MMP plays a crucial role in capturing both dominant and weaker multipath components by systematically evaluating all potential basis functions at a given level before progressing further. The basis functions, representing key OTFS parameters are selected based on their correlation with the residual signal. Unlike conventional greedy approaches and DF-MMP, the BF-MMP simultaneously considers multiple basis functions, leading to a more robust and accurate CE process. A significant advantage of BF-MMP in OTFS CE is its ability to provide a broader search space, ensuring that relevant channel coefficients are identified early in the estimation process. This is particularly beneficial in dynamic environments with rapidly varying mobility, where accurate Doppler estimation is critical for reliable data recovery. The BF approach mitigates the risk of suboptimal selections that could arise from a strictly sequential search. However, this simultaneous exploration requires greater computational resources compared to DF-MMP, as multiple paths are processed in parallel. The effectiveness of BF-MMP in achieving high-precision CE while maintaining a balance between accuracy and computational complexity is discussed in the next section.

Algorithm 2 BF-MMP

Input: Measurement $\mathbf{y}$, sensing matrix $\mathbf{\Psi}$, sparsity K, number of paths L
Output: Estimated signal $\hat{\mathbf{h}}$
Initialization: $k := 0$ (iteration index), $\mathbf{r}^0 := \mathbf{y}$ (initial residue), $\Omega := \{\emptyset\}$
while $k < K$ **do**
  $k := k+1$, $u = 0$, $\Omega^k = \emptyset$
  for $i = 1$ **to** $|\Omega^{k-1}|$ **do**
    $\widetilde{\pi} := \arg\max_{|\pi|=L} \|(\mathbf{\Psi}'\mathbf{r_i^{k-1}})_\pi\|_2^2$
    for $j = 1$ **to** L **do**
      $\Omega_{temp} := \Omega_{\mathrm{i}}{}^{k-1} \cup \{\widetilde{\pi}_j\}$
      if $\Omega_{temp} \notin \Omega^k$ **then**
        $u := u+1$
        $\Omega_u^k := \Omega_{temp}$
        $\Omega^k := \Omega^k \cup \{\Omega_u^k\}$
        $\hat{\mathbf{h}}_u^k := \mathbf{\Psi}^\dagger_{\Omega_u^k}\mathbf{y}$
        $\mathbf{r}_u^k := \mathbf{y} - \mathbf{\Psi}^\dagger_{\Omega_u^k}\hat{\mathbf{h}}_u^k$
      end if
    end for
  end for
end while
$u^* := \arg\min \|\mathbf{r_u^k}\|_2^2$
$\Omega^* := \Omega_{u^*}^K$
return $\hat{\mathbf{h}} := \mathbf{\Psi}^\dagger_{\Omega^*}\mathbf{y}$

TABLE I
VLC CHANNEL MODELING PARAMETERS

Parameters	Values
Carrier Frequency	$2.15 \times 10^9 Hz$
Duplex mode	FDD
Subcarrier spacing	$15KHz$
FFT size	1024
No. of resource block	50
Size of a OTFS frame (M, N)	$(600, 12)$
No. of BS antenna	32
No. of user antenna	1
Channel model : 3GPP SCM	Urban macro cell
No. of dominant channel paths	6
No. of sub-path per dominant path	20
User velocity	$100m/s$

IV. Results and Discussions

The considered system model is analysed in terms of NMSE through DF and BF MMP for various transmit signal-to-noise ratio (SNR). Table I displays the key simulation parameters utilized for the analysis of OTFS modulation. The urban macro cell scenario with frequency division duplexing (FDD) consisting of 6 dominant paths which in turn cover 20 sub-paths in each dominant path are accounted for simulation. The impact of pilot overhead, number of base station antennas, and user velocity are also analysed for MMP-based CE. Moreover, the outcomes of the MMP- based approach are correlated with the impulse and OMP-based techniques and the performance in terms of NMSE is discussed. NMSE is a measure that evaluates the accuracy of an estimation problem by quantifying the difference between predicted and actual values. The NMSE of the proposed MMP-based channel estimation technique is computed as,

$$\mathrm{NMSE} = \frac{\|\hat{\mathrm{H}} - \mathrm{H}\|^2}{\|\mathrm{H}\|^2} \tag{15}$$

The NMSE performance of DF and BF MMP techniques with impulse and OMP approaches are traced in Fig. 1. Monte Carlo (MC) simulations with 10^5 iterations were performed to evaluate the NMSE performance of the CE techniques for OTFS. The simulations accounted for varying system parameters, including Doppler shifts, delay spreads, and pilot overhead, ensuring comprehensive performance validation. The numerical results obtained from these simulations confirm the effectiveness and robustness of the proposed approach in different channel conditions. Immediate inference on transmit SNR and NMSE shows that they are inversely proportional to each other and MMP-based CE techniques contribute to less error than OMP and impulse methods. This is because the OMP performs sequential correlation by considering only a single basis function and updates the residual parameter iteratively till the exact match is found. Moreover, the impulse technique involves the pilot transmission and adopts least square methods for CE which increases the interference thereby contributing to a high error rate. Keen observation reveals that the DF-MMP technique outperforms BF-MMP in terms of NMSE for the considered simulation parameters because only a single dominant path is chosen for this analysis. However, if the number of dominant paths and sub-paths

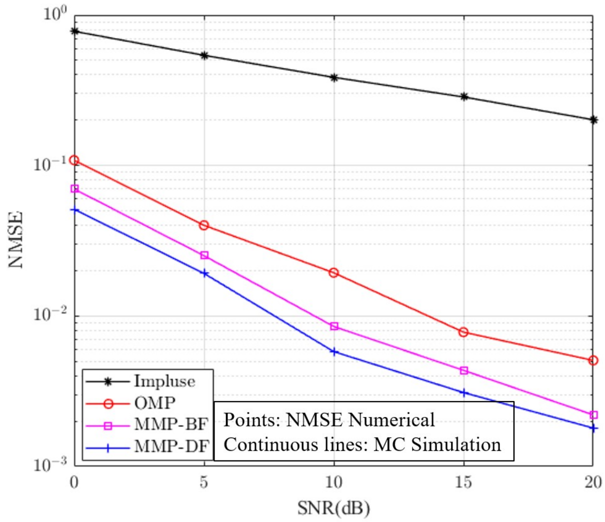

Fig. 1. NMSE performance of CE schemes validated through MC simulations against various SNR

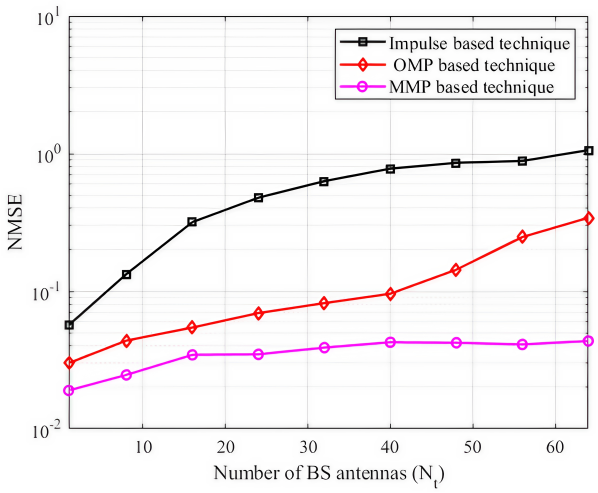

Fig. 2. NMSE performance comparison for CE techniques against the number of BS antennas

within each dominant is increased, BF-MMP outperforms DF-MMP since the search happens simultaneously in the former. On average, the MMP technique offers a gain of 4 dB over the OMP technique for the error of 10^{-2}.

Figure 2 displays the NMSE performance of MMP-based CE aiding various base station antennas and compared with OMP and impulse methods for a transmit SNR of 10 dB. The NMSE gets high as the number of base station antennas increases due to interference among multiple antennas. Inference shows that the MMP technique possesses an error rate of 0.04 for 10 antennas, whereas for the same number of antennas, the error of 0.07 and 0.2 is observed in OMP and impulse, respectively. Likewise, if 30 antennas are aided at the base station, errors of 0.06, 0.09, and 0.8 account for MMP, OMP, and impulse techniques, respectively.

The pilot overhead ratio analysis ranging from 20% to 60%

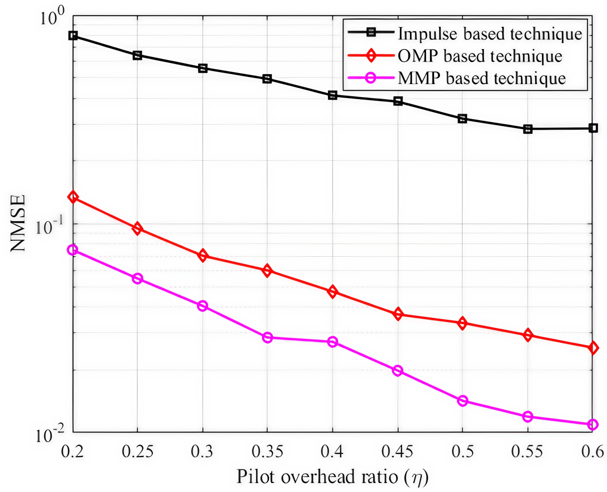

Fig. 3. NMSE performance comparison for CE techniques against pilot overhead ratio

for MMP-based CE is sketched out in Fig. 3, which infers that the NMSE is inversely proportional to the pilot overhead ratio. This is because as the number of pilot overhead increases more probability of exact correlation of basis function occurs and in turn estimation error decreases. Profound observation shows that the MMP technique outperforms OMP and impulse methods due to the ability of simultaneous and deep correlation of basis function by MMP. An error gain of 0.03 and 0.47 is achieved by MMP over OMP and impulse techniques, respectively for constant pilot overhead of 50%.

The key benefit of OTFS modulation is its ability to model the channel in high fading or dynamic environments, i.e., OTFS aids for the DD domain localization which is time-invariant in nature. Figure 4 shows the estimation error performance at various user velocities which is analyzed for the MMP technique and the same is compared with OMP and impulse-based CE for an SNR of 10dB. Observation implies that the error gets higher as the user velocity increases which is due to the Doppler spread in the channel. To be precise, in the case of MMP-based CE at a velocity of 40m/s, the achieved NMSE is 0.02 whereas, for 100m/s it is 0.05 and the performance is superior to OMP and impulse-based methods which achieve 0.07, 0.7, and 0.08, 0.8, respectively.

The computational complexity of CE techniques plays a crucial role in determining their feasibility for OTFS in practical high-mobility scenarios. In this paper, the complexity of DF-MMP, BF-MMP, OMP, and impulse-based estimation methods are analyzed. The DF-MMP follows a sequential path selection approach where the algorithm prioritizes a single most dominant path at each iteration, refining it before considering alternative paths. The complexity of DF-MMP is primarily influenced by the number of iterations and the search depth. Without loss of generality, if the number of multipath components in the DD domain is L, and assuming the search depth to be D, the computational complexity is $\mathcal{O}(D \cdot L \cdot N)$ where N represents the number of pilot symbols used for estimation. Since DF-MMP explores one path at a time,

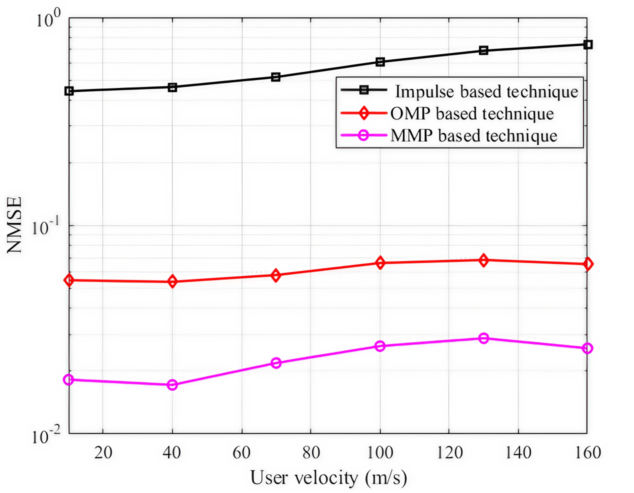

Fig. 4. NMSE performance comparison for CE techniques at various velocities

it achieves lower complexity compared to BF-MMP while maintaining a structured search strategy. However, its reliance on path ordering can sometimes lead to local optima. BF-MMP, in contrast, explores multiple potential paths in parallel at each iteration before refining the best candidates. This leads to a more exhaustive search, enhancing accuracy at the cost of increased computational complexity. The complexity of BF-MMP is influenced by the number of candidate paths considered per iteration. Assuming B candidate paths are evaluated at each step, the complexity can be approximated a $\mathcal{O}(B \cdot L \cdot N)$. Since $B > D$, BF-MMP typically has a higher complexity than DF-MMP. However, it provides better robustness against erroneous path selection and improves overall channel estimation accuracy at the expense of greater computational resources. Whereas, OMP follows a greedy approach by selecting the most correlated basis vector at each iteration and orthogonalizing the residual signal accordingly. The computational complexity of OMP can be driven by the number of iterations required to reconstruct the sparse channel. For an OTFS system with L significant paths and a dictionary matrix of size $M \times N$, the complexity is $\mathcal{O}(L \cdot M \cdot N)$ OMP provides a moderate trade-off between complexity and accuracy but does not explicitly exploit the structured multipath nature of OTFS channels, leading to potential performance limitations. In contrast, traditional impulse-based techniques rely on direct correlation with known pilot signals to estimate the channel impulse response. This method avoids iterative computations and has the lowest computational cost among the analyzed techniques. The complexity is mainly dictated by the number of pilot symbols and can be expressed as $\mathcal{O}(N)$. Since impulse-based methods do not exploit the sparsity of the DD domain, their performance degrades significantly in high-mobility environments, making them less suitable for OTFS. Among the analyzed techniques, DF-MMP achieves a favorable balance between computational complexity and estimation accuracy, making it a strong candidate for OTFS CE. BF-MMP provides better accuracy but comes at a higher computational cost. OMP, while moderately complex, lacks structured multipath tracking, making it sub-optimal for OTFS. Impulse-based estimation, though computationally efficient, suffers from severe performance degradation in high-mobility scenarios. Thus, for practical OTFS implementations, DF-MMP emerges as the best choice due to its structured approach, lower complexity compared to BF-MMP, and superior ability to recover the sparse DD channel.

V. Conclusion

This paper investigated MMP-based algorithms (BF-MMP and DF-MMP) for CE in OTFS systems, highlighting the benefits of the CS greedy approach and utilizing MMP's unique properties for OTFS modulation. Extensive analysis demonstrated the superiority of MMP over conventional methods, particularly in scenarios with high Doppler spread and severe delay spread. The results prove that MMP achieved robust CE even under challenging conditions such as high mobility, frequency-selective fading, and varying pilot overhead. Additionally, the impact of key parameters, including user velocity, pilot overhead ratio, and multiple antennas at the base station, was examined. These findings contributed to advancing OTFS CE, improving signal detection accuracy, and enhancing overall system reliability in 5G and beyond wireless networks. Future research may focus on optimizing MMP further, exploring adaptive algorithms for dynamic parameter tuning, and investigating advanced signal processing techniques integrated with machine learning to enhance estimation accuracy in rapidly changing environments.

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